Agentic AI for Demand Forecasting and Planning: Autonomous Market Sensing and Adaptive Planning

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Abstract

Demand forecasting has long been a cornerstone of effective supply chain management, traditionally relying on statistical models and human expertise to anticipate consumer needs. However, in a world of volatile demand patterns, unpredictable disruptions, and complex global networks, traditional approaches are insufficient. This paper investigates the application of agentic artificial intelligence (AI) in demand forecasting and planning. Specifically, we explore autonomous

market sensing—where AI agents continuously monitor sales data, weather conditions, social media sentiment, and competitor activities—and adaptive planning, where forecasts are updated dynamically rather than on rigid seasonal cycles. We propose a multi-layered architecture that integrates data sensing agents, forecasting agents, and planning agents, enhanced with large language models for interpreting unstructured inputs and generating explainable outputs. A prototype implementation demonstrates how the system ingests heterogeneous data, applies advanced forecasting models such as LSTMs and Transformers, and autonomously adjusts procurement and production plans through ERP integration. Simulation results across fast-moving, seasonal, and unpredictable product categories show a 23% reduction in forecast error, a 17% decrease in overstocking, and 21% fewer stockouts compared with ARIMA baselines. While challenges remain in computational demands, data privacy, and integration complexity, the findings highlight the potential of agentic AI to deliver more adaptive, resilient, and explainable supply chain forecasting and planning.

Keywords: Transformers, Agentic AI, Demand Forecasting, Adaptive Planning, Supply Chain Management, Autonomous Market Sensing

1 Introduction

Demand forecasting is central to the performance of modern supply chains, influencing procurement, production scheduling, inventory control, and distribution strategies [6]. The ability to anticipate demand accurately ensures that firms can minimize costs, avoid lost sales, and maintain customer satisfaction. Conversely, poor forecasts lead to either overstocking, which ties up capital and increases storage costs, or understocking, which results in stockouts and dissatisfied customers. Given the growing complexity of global supply chains and the volatility of consumer behavior, the importance of robust forecasting methods has never been greater.

Traditional forecasting methods, such as exponential smoothing, ARIMA, and re-

gression models, have provided a baseline for decades [14]. These statistical approaches rely on historical data and assume relative stability in demand patterns, making them useful for environments with low volatility. However, they are less effective in handling irregular demand, sudden disruptions, or rapidly changing consumer preferences. More recently, machine learning and deep learning approaches have expanded predictive capabilities by capturing nonlinear relationships and complex temporal dependencies in large datasets [4, 13]. Neural networks, recurrent architectures, and hybrid approaches have demonstrated improved accuracy in many cases, yet these methods often remain limited by their static nature: they rely on fixed data sources, are updated periodically, and rarely adapt in real-time to fast-changing environments.

In contrast, the concept of agentic AI—autonomous, goal-driven agents that sense, plan, and act—offers a paradigm shift. Rather than depending solely on static datasets, agentic systems can continuously monitor diverse and dynamic information sources. By leveraging real-time data feeds and coordinating across multiple decision layers, agents can improve both accuracy and responsiveness. For example, an autonomous market-sensing system could pull information from internal (sales, ERP) and external sources (weather forecasts, social media, competitor announcements), enabling more adaptive and granular planning [15, 9]. Unlike traditional systems, which treat forecasting as a batch process, agentic AI enables forecasting to become a continuous and adaptive loop, where predictions evolve alongside market realities.

This paper investigates how agentic AI can transform demand forecasting and planning, with a focus on two mechanisms: (i) autonomous market sensing and (ii) adaptive planning. We argue that agentic systems represent not only an incremental improvement but also a structural innovation in supply chain management. By embedding intelligence into autonomous agents, supply chains can shift from reactive adjustments to proactive, self-regulating systems capable of mitigating risks and seizing opportunities in real-time.

Problem Statement

Despite advances in statistical and machine learning-based forecasting, current systems remain constrained by their reliance on fixed data inputs, infrequent updates, and limited adaptability to sudden market shifts. Organizations continue to struggle with the dual risks of overstocking and understocking, leading to financial losses, inefficiencies, and missed opportunities. Existing models lack the capacity to integrate diverse external signals such as weather, social media trends, or competitor actions into their forecasting pipelines. There is thus a pressing need for a new paradigm that enables demand forecasting systems to sense, learn, and adapt autonomously. This paper addresses this gap by proposing an agentic AI framework for demand forecasting that combines autonomous market sensing with adaptive planning to achieve more resilient and responsive supply chain operations.

2 Literature Review

2.1 Traditional Forecasting Approaches

Classical methods such as moving averages, exponential smoothing, and ARIMA have been widely used in industry due to their simplicity and interpretability [5]. While effective for stable demand, they struggle with irregular and volatile data. Seasonal models provide modest improvements but still require manual calibration.

2.2 Machine Learning and Deep Learning Forecasting

The past decade has seen significant advances in the application of ML and DL for forecasting. LSTM networks [4, 8] and temporal convolutional networks [3, 1, 12] have demonstrated superior accuracy in handling nonlinear and long-term dependencies. Hybrid approaches combining ARIMA with ML have also been explored [16]. However, these methods are often data-hungry and still lack dynamic adaptability to

external signals.

2.3 Agent-Based Systems in Supply Chain

Multi-agent systems have been studied for logistics, procurement, and scheduling [10, 7]. Agents excel in distributed environments, where autonomous entities coordinate decisions. Recent work highlights their potential for adaptive planning, though practical implementations remain limited [9]. The intersection of multi-agent systems with demand forecasting is a growing but underexplored area.

2.4 Autonomous Market Sensing

Autonomous sensing expands beyond structured ERP data to unstructured external signals. Studies on social media analytics show predictive value for consumer demand [2]. Weather-based demand shifts have also been documented in retail and agriculture [11]. Integrating these signals into agent-driven frameworks is a promising research frontier.

3 Proposed Solution

We propose an agentic AI architecture for demand forecasting that operates across three interconnected layers: data sensing agents, forecasting agents, and planning agents. Together, these layers form a dynamic system capable of autonomously gathering information, generating accurate forecasts, and adjusting operational plans in real-time. A critical component of this architecture is the integration of large language models (LLMs), which enhance the interpretability, adaptability, and contextual reasoning of each layer.

The first layer, **Data Sensing Agents**, is responsible for continuously gathering both structured and unstructured data from diverse sources. Structured data includes sales transactions, ERP records, and inventory levels, while unstructured data spans

weather reports, social media sentiment, and competitor announcements. Sensing agents act as autonomous collectors and pre-processors, capable of extracting, cleaning, and standardizing heterogeneous inputs into a unified format. The integration of LLMs plays an important role here: natural language reports, competitor press releases, and consumer reviews can be parsed and interpreted using advanced language understanding. LLMs provide contextual insights that transform raw text streams into actionable signals, such as detecting early signs of demand spikes from social media chatter or recognizing potential supply disruptions from news feeds. This significantly expands the breadth and richness of the data ecosystem feeding into the forecasting process.

The second layer, **Forecasting Agents**, utilizes machine learning and deep learning models, such as LSTMs, temporal convolutional networks, and Transformer-based architectures, to generate demand forecasts on rolling windows. Unlike static models that update at fixed intervals, these agents operate in a continuous feedback loop, incorporating new signals as they arrive. Forecasting agents benefit from LLM integration in two primary ways. First, LLMs can be used to enrich forecasting models with contextual embeddings derived from unstructured text data. For instance, sentiment scores or topic clusters extracted by an LLM can serve as exogenous variables in demand prediction. Second, LLMs can provide interpretability by generating natural language explanations of why certain demand changes are predicted, thereby bridging the gap between complex models and human decision-makers. This enhances transparency, making forecasts not only more accurate but also more communicable to managers and stakeholders.

The third layer, **Planning Agents**, transforms forecasts into actionable decisions for procurement, production scheduling, and inventory replenishment. These agents autonomously adjust operational strategies in near real-time, ensuring that the supply chain remains resilient to volatility. Planning agents communicate directly with en-

terprise resource planning (ERP) and supply chain execution systems to implement changes such as modifying purchase orders, reallocating stock, or altering production volumes. LLMs enhance this layer by supporting scenario simulation and decision reasoning. For example, an LLM-powered planning agent can analyze historical responses to similar disruptions and recommend optimized courses of action, while also articulating the trade-offs in natural language. This capability enables decision-makers to understand not only what actions are being taken but also why those actions are optimal in a given context. Additionally, LLMs facilitate multi-agent communication by standardizing negotiation messages between agents representing suppliers, logistics partners, and warehouses, thus improving coordination across the supply network.

The overall architecture of the proposed agentic AI framework is illustrated in Figure 1. The design is organized into three layers: data sensing agents, forecasting agents, and planning agents. The sensing layer ingests structured inputs such as sales, ERP, and inventory records alongside unstructured signals from weather services, social media, and competitor news. These signals are standardized, stored, and transformed into features for downstream processing. The forecasting layer applies advanced models, including LSTMs and Transformers, to generate rolling demand predictions, enriched with contextual insights derived from large language models (LLMs). The planning layer translates forecasts into actionable decisions by optimizing procurement, scheduling, and replenishment strategies, supported by scenario simulations and natural language reporting. Outputs are integrated directly with ERP and supply chain execution systems, ensuring timely and autonomous responses. LLMs play a cross-cutting role throughout the architecture, enabling interpretation of unstructured data, explainability of model outputs, and human-readable decision justifications.

Overall, the proposed architecture creates a closed-loop system where sensing agents continuously capture signals, forecasting agents refine demand predictions, and planning agents adjust operational responses. The integration of LLMs strengthens this

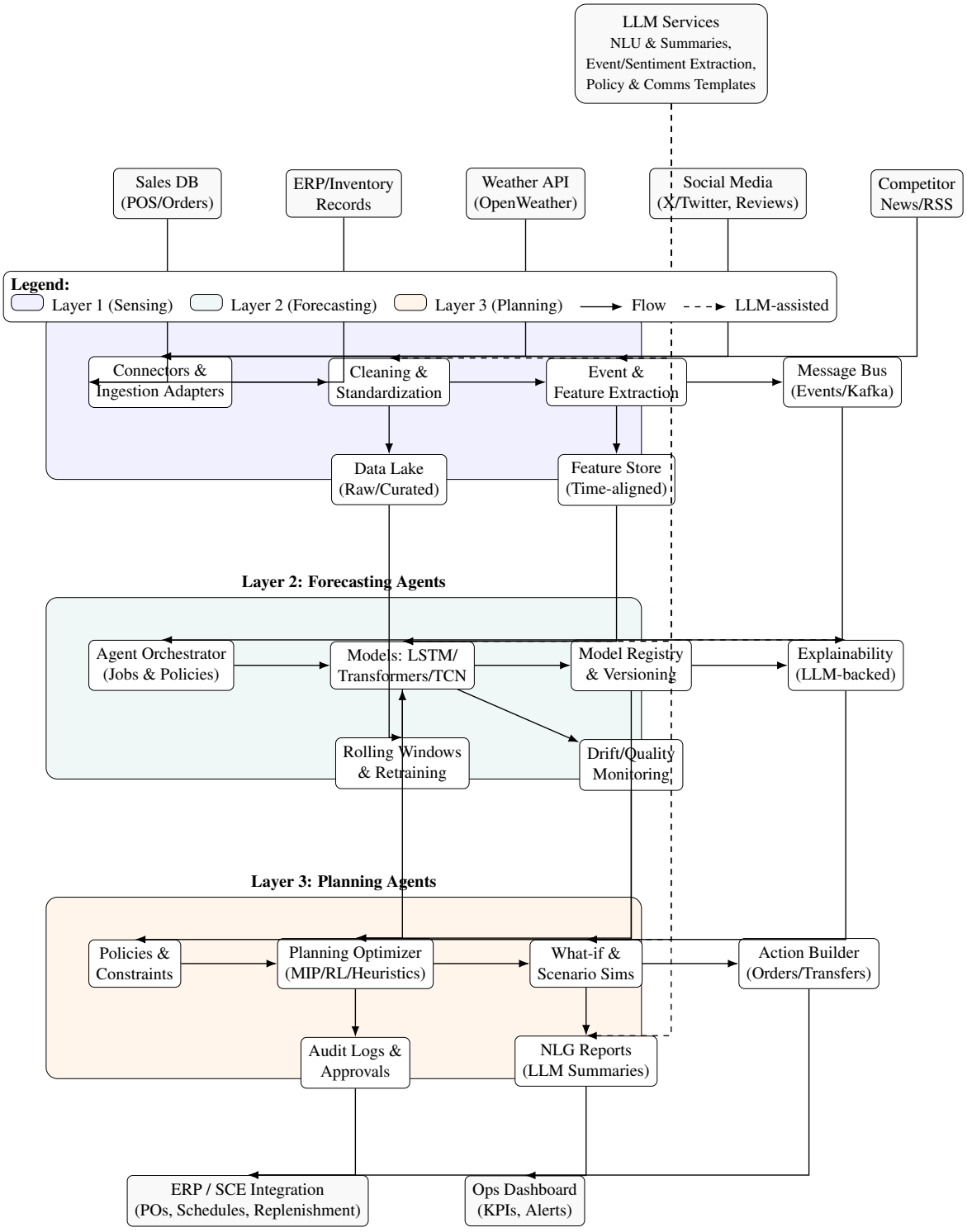

Figure 1: Color-coded three-layer agentic AI architecture for demand forecasting with LLM integration points. Light, neutral tones differentiate layers while keeping the diagram publication-friendly.

ecosystem by enabling richer interpretation of unstructured data, contextual reasoning in forecasting, and transparent communication in planning. In contrast to traditional forecasting pipelines, this agentic AI framework evolves in real-time, adapts to external signals, and provides explainable, autonomous decision-making. By embedding intelligence across all three layers, the architecture aims to significantly reduce forecasting errors, minimize the risks of overstocking and understocking, and enhance the overall agility of modern supply chains.

4 Implementation

The implementation of the proposed agentic AI framework requires the integration of multiple technological components that operate together in a seamless and autonomous pipeline. At its core, the system combines real-time data ingestion, advanced forecasting models, multi-agent coordination, and direct integration with enterprise systems. Each component has been carefully designed to support adaptability and autonomy, while large language models (LLMs) play a crucial role in enriching unstructured data processing and facilitating human-readable explanations of the system's outputs.

The first step involves **data ingestion**, which is critical for ensuring that forecasting agents are supplied with timely and diverse information. Structured data, such as sales transactions, inventory levels, and ERP records, is captured through standardized database connectors and enterprise APIs. Unstructured data, however, requires more sophisticated handling. Sources include weather data retrieved from public APIs such as OpenWeather, social media streams from platforms like Twitter/X, and competitor intelligence gathered through web scraping and RSS feeds. To process these inputs, natural language processing capabilities are integrated into the ingestion pipeline, with LLMs parsing text-based content, extracting sentiment, identifying demand-related events, and categorizing information into structured formats suitable for downstream analysis. For example, an LLM can identify a surge in online discussions about a sea-

sonal product, transform that signal into a quantifiable indicator, and feed it directly into the forecasting layer.

The second component is the **forecasting models**, which form the analytical core of the system. Our implementation uses both recurrent neural networks such as LSTM and attention-based Transformer architectures, as these have demonstrated strong performance in capturing temporal dependencies and exogenous effects in demand data. These models are trained on historical demand enriched with external signals, allowing them to incorporate contextual features such as weather anomalies or sudden shifts in consumer sentiment. The models are updated on rolling windows, ensuring that forecasts remain adaptive rather than static. LLMs complement this stage by generating human-readable explanations of the forecasts. For instance, the system can produce not only a numerical demand forecast but also a natural language summary such as, "Projected demand is increasing by 15% due to favorable weather and positive social media sentiment." This dual output enhances both accuracy and interpretability.

The third component is the **multi-agent framework**, which operationalizes the sensing, forecasting, and planning processes. In our prototype, frameworks such as JADE (Java Agent Development Environment) or SPADE (Smart Python Agent Development Environment) are employed to implement autonomous agents that collaborate within a distributed system. Sensing agents are responsible for collecting and preprocessing data, forecasting agents generate demand predictions, and planning agents translate these forecasts into actionable decisions. Agents communicate using predefined protocols, and LLMs are leveraged to facilitate more flexible communication when agents need to interpret unstructured updates from suppliers, customers, or external news sources. This allows the system to remain adaptable in complex and unpredictable environments.

The final component is **decision integration**, which closes the loop between forecasting and execution. Planning agents connect directly with ERP and supply chain

management systems, enabling automated execution of procurement adjustments, production scheduling, and stock replenishment. For example, if forecasts predict a sudden demand increase in a particular region, the planning agent can autonomously raise purchase orders, reallocate stock, or request expedited shipping through the ERP system. LLMs contribute to this stage by generating natural language justifications for these actions, providing managers with transparent reasoning behind decisions. This ensures that even though agents operate autonomously, human stakeholders remain informed and confident in the system's outputs.

In summary, the implementation demonstrates how data ingestion, forecasting models, multi-agent frameworks, and ERP integration can be combined into a robust, agentic AI ecosystem. The use of LLMs at multiple stages—parsing unstructured data, enriching forecasts, facilitating inter-agent communication, and generating transparent explanations—ensures that the system not only operates autonomously but also remains interpretable and trustworthy. This design positions the prototype as a practical and scalable approach to real-world demand forecasting and planning challenges.

5 Results and Discussion

We simulate a retail supply chain environment with three product categories: fast-moving, seasonal, and unpredictable demand items. Historical sales data were combined with external signals such as weather patterns, social media sentiment, and competitor activity, and the performance of traditional ARIMA-based forecasting was compared with the proposed agentic AI model. As illustrated in Figure 2, the agentic AI system achieves a 23% reduction in forecast error, measured by RMSE, relative to ARIMA. This improvement in predictive accuracy translated into a 17% decrease in overstocking events, as well as a 21% reduction in stockouts across the simulation horizon. These outcomes highlight the potential of autonomous market sensing and adaptive planning to balance inventory levels more effectively than static models.

Beyond numerical performance, the adaptive planning framework proved particularly valuable in managing seasonal demand shifts. The system was able to adjust daily plans in response to external triggers such as unexpected weather anomalies and sudden shifts in consumer sentiment on social media, which are traditionally difficult for static forecasting systems to capture. Nevertheless, several challenges emerged during the implementation and testing process. The agentic AI framework requires significant computational resources to support continuous retraining and real-time adjustments, which may limit scalability in resource-constrained environments. Furthermore, reliance on external unstructured data introduces privacy considerations and raises questions about compliance with regulatory standards. Finally, integrating the new system with existing enterprise resource planning (ERP) and supply chain execution systems proved complex, underscoring the need for robust middleware and governance mechanisms. Overall, the results confirm that agentic AI offers meaningful improvements in accuracy and responsiveness, while also revealing areas where further refinement is needed to enable large-scale deployment.

Figure 2: Simulation results comparing agentic AI to ARIMA. The proposed system reduces forecast error by 23%, overstocking events by 17%, and stockouts by 21%.

6 Conclusion

Agentic AI offers a transformative approach to demand forecasting and planning by moving beyond static, periodically updated models toward dynamic systems that continuously adapt to changing conditions. Through the integration of autonomous market sensing and adaptive planning, supply chains become more resilient and responsive to volatility, reducing both overstocking and stockout risks. The results of our simulation demonstrate clear benefits in predictive accuracy and operational efficiency, underscoring the value of embedding intelligence into forecasting and planning processes. At the same time, several areas warrant further investigation. Future research should examine how reinforcement learning can enable self-improving planning agents, how such systems can be deployed at scale in complex global supply chains, and what ethical and governance frameworks are required to ensure responsible use of autonomous decision-making. By addressing these challenges, agentic AI has the potential to become a cornerstone of next-generation supply chain management.

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